



COST FUNCTIONS IN FUZZY ANALYSIS CLUSTERING

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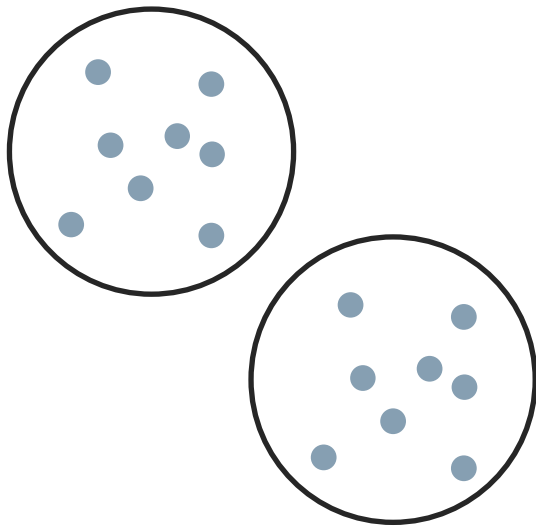
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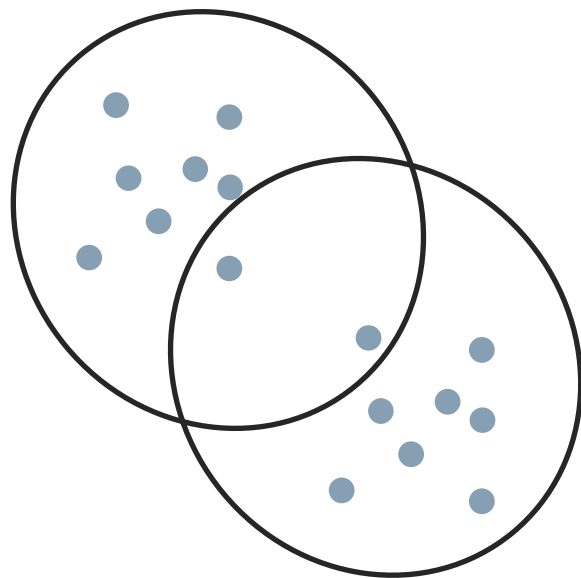
BASIC IDEA

- Fuzzy C-means clustering is a soft clustering algorithm where a data point can be assigned to more than one cluster using membership values.
- In simple terms, the objective (cost) function is a correctional function that measures the quality of the clustering by analyzing how wrong the cluster designations are.
- The process of clustering is to optimize this objective function.
- It is a weighted average of cluster variances, with weights that are proportional to cluster size in terms of the number of points.

VISUALIZE



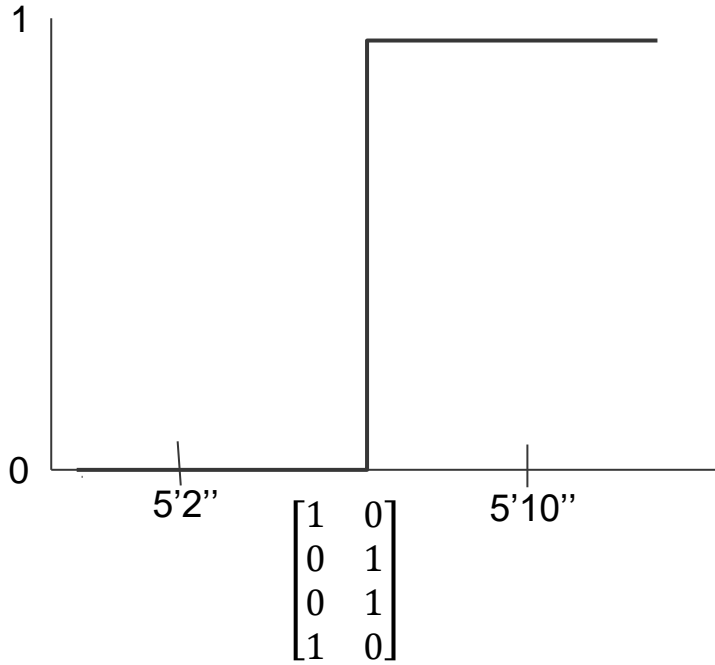
VISUALIZE



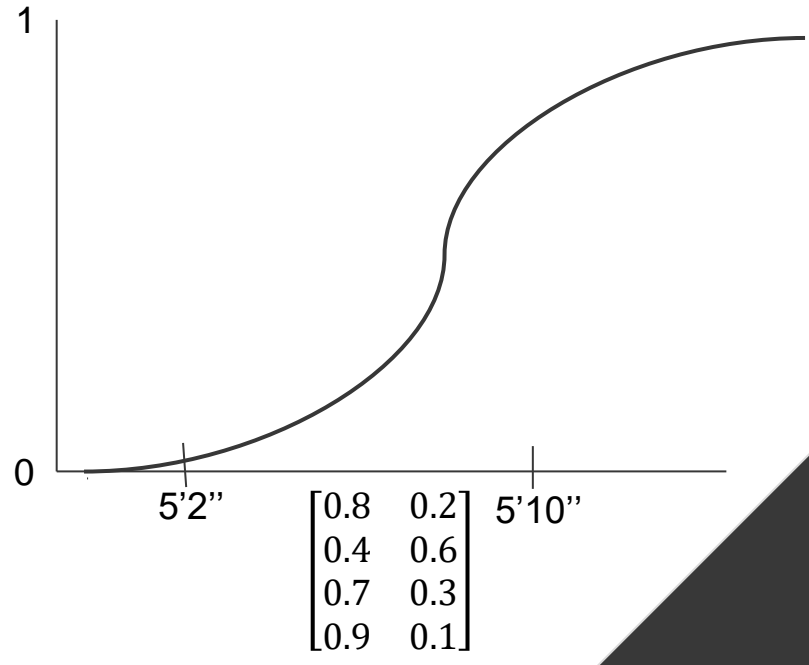
MEMBERSHIP FUNCTION

- What is the membership value for each data point to each cluster?
 - Falls between 0 to 1.

K-Means



C-Means



FUZZY LOGIC

- In standard binary problems, a statement is either True or False... there is no in-between.
- Using fuzzy logic.. A statement can be True with an associated membership value and False with an associated membership value.

BASIC CONCEPTS

$$0 \leq u_{ij} \leq 1 \quad \forall \quad u_{ij}$$

Membership Value for each point

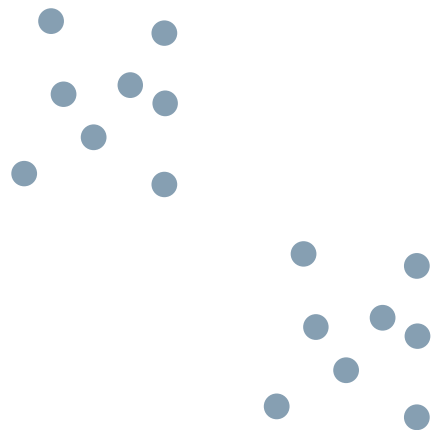
$$\sum_{j=1}^c u_{ij} = 1 \quad \forall \quad c = 1, 2, \dots, n$$

Cluster level summation

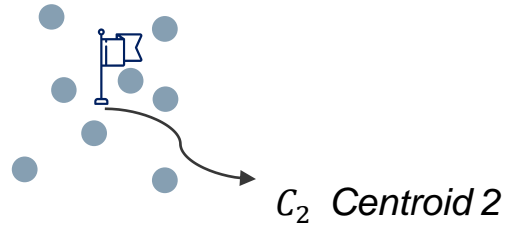
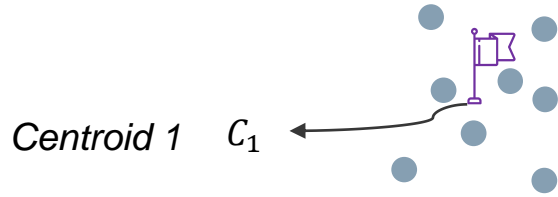
$$0 < \sum_{i=1}^n u_{ij} < n \quad \forall \quad j = 1, 2, \dots, c$$

Point level summation

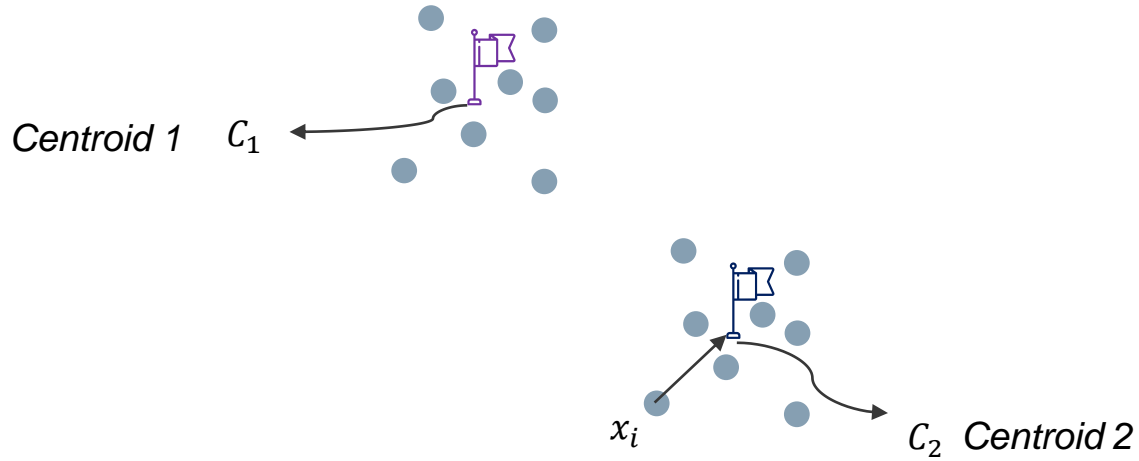
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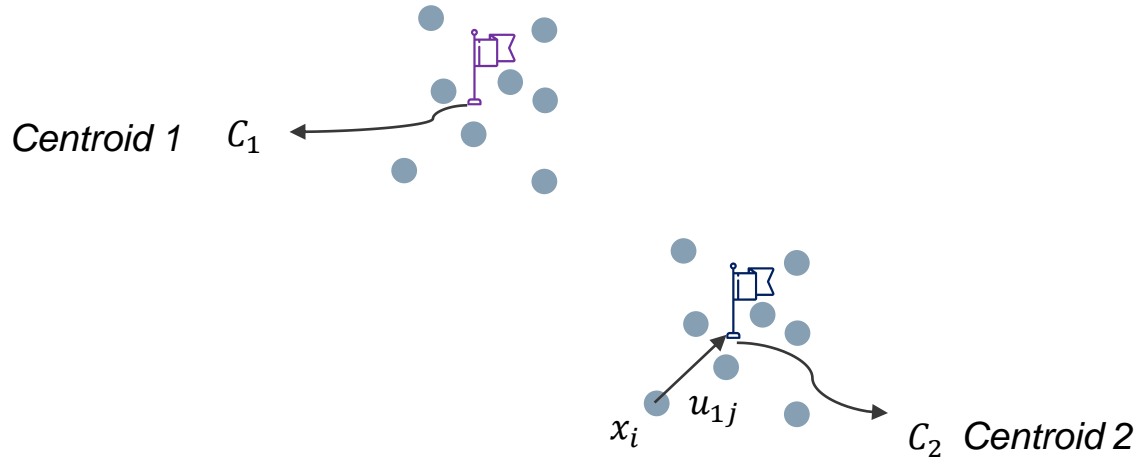
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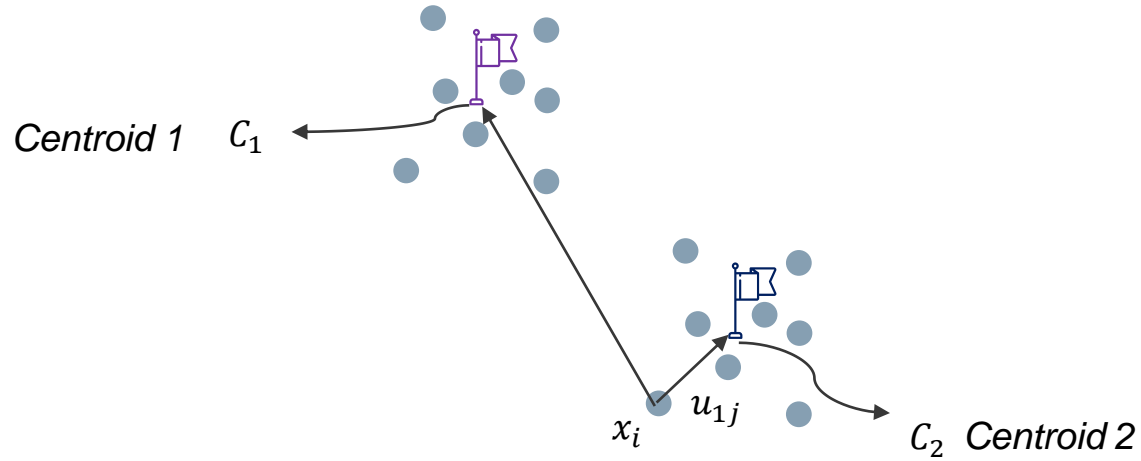
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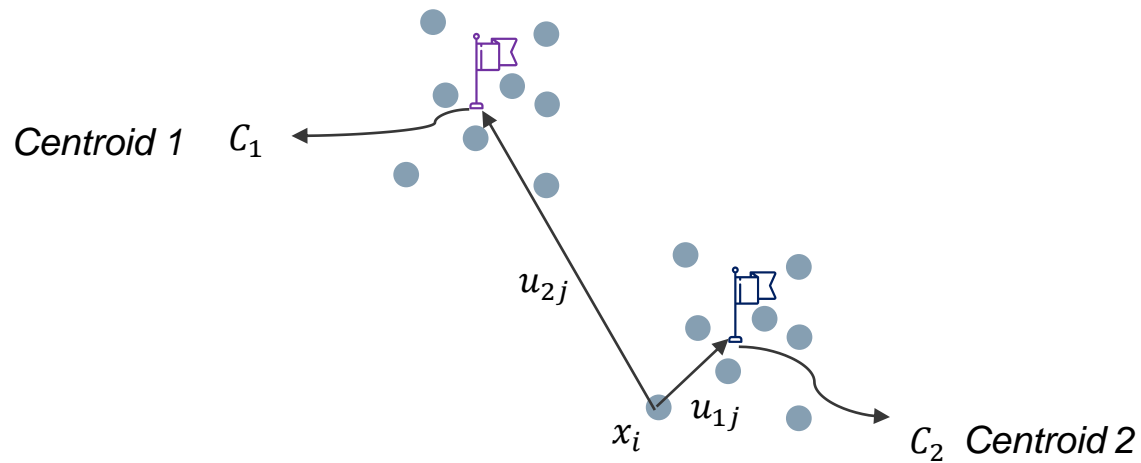
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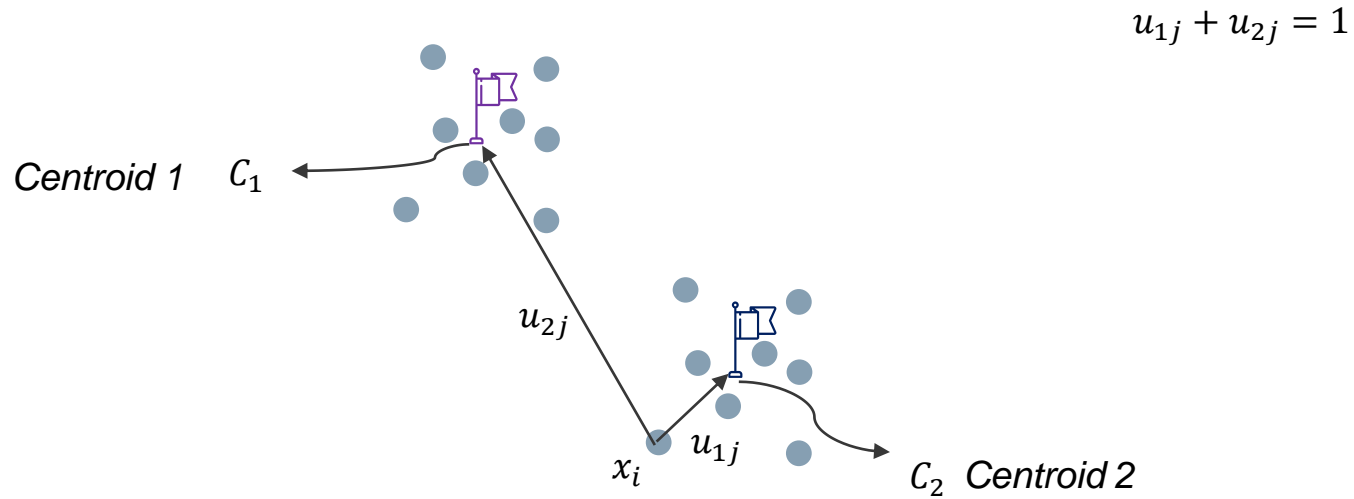
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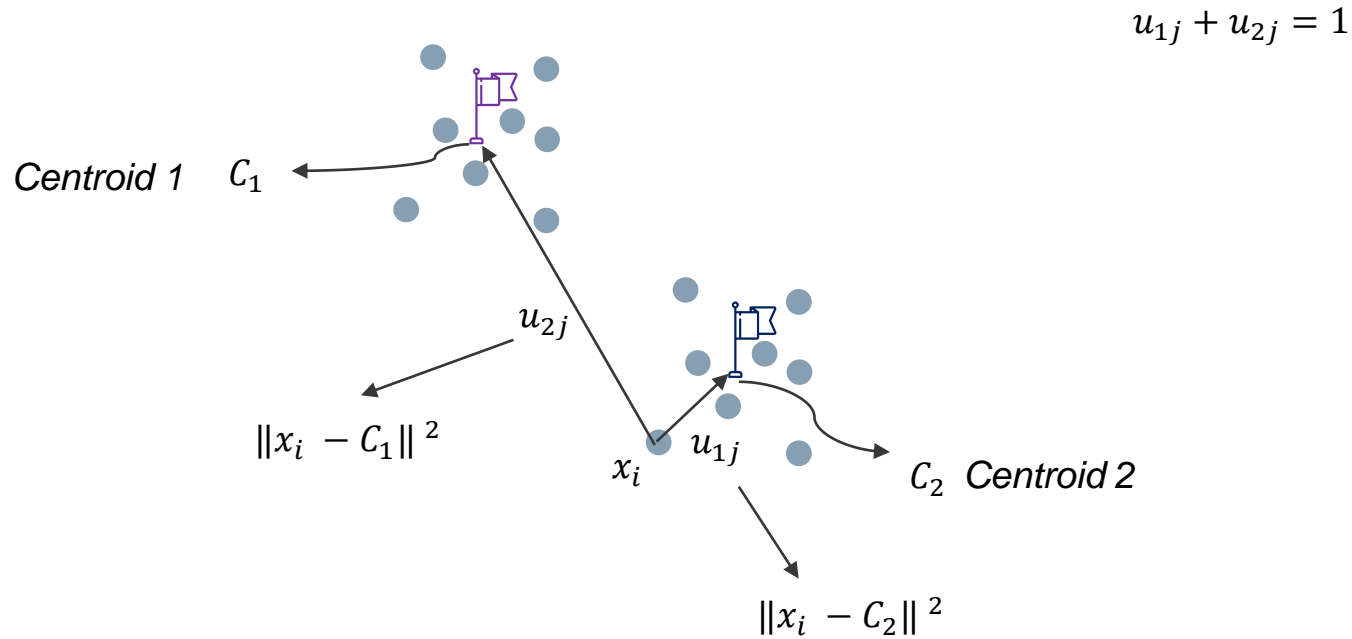
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TRIANGLE INEQUALITY

$$\begin{aligned}\|x_i - C_1\|^2 &= \langle x_i - C_1, x_i - C_1 \rangle \\&= \|x_i\|^2 - \langle x_i, C_1 \rangle - \langle C_1, x_i \rangle - \|C_1\|^2 \text{ where } \langle C_1, x_i \rangle = \overline{\langle x_i, C_1 \rangle} \\&= \|x_i\|^2 - 2\operatorname{Re}\langle x_i, C_1 \rangle - \|C_1\|^2 \\&\leq \|x_i\|^2 - 2|\langle x_i, C_1 \rangle| - \|C_1\|^2 \\&\leq \|x_i\|^2 - 2\|x_i\|\|C_1\| - \|C_1\|^2 \\&= (\|x_i\| - \|C_1\|)^2\end{aligned}$$

Taking the square roots gives the triangle inequality

$$\|x_i - C_1\| \leq \|x_i\| - \|C_1\|$$

OBJECTIVE (COST) FUNCTION

$$J_m(u_{ij}, c_i) = \sum_{i=1}^N \sum_{j=1}^C u_{ij}^m \|x_i - c_j\|^2$$

Let $m > 1$

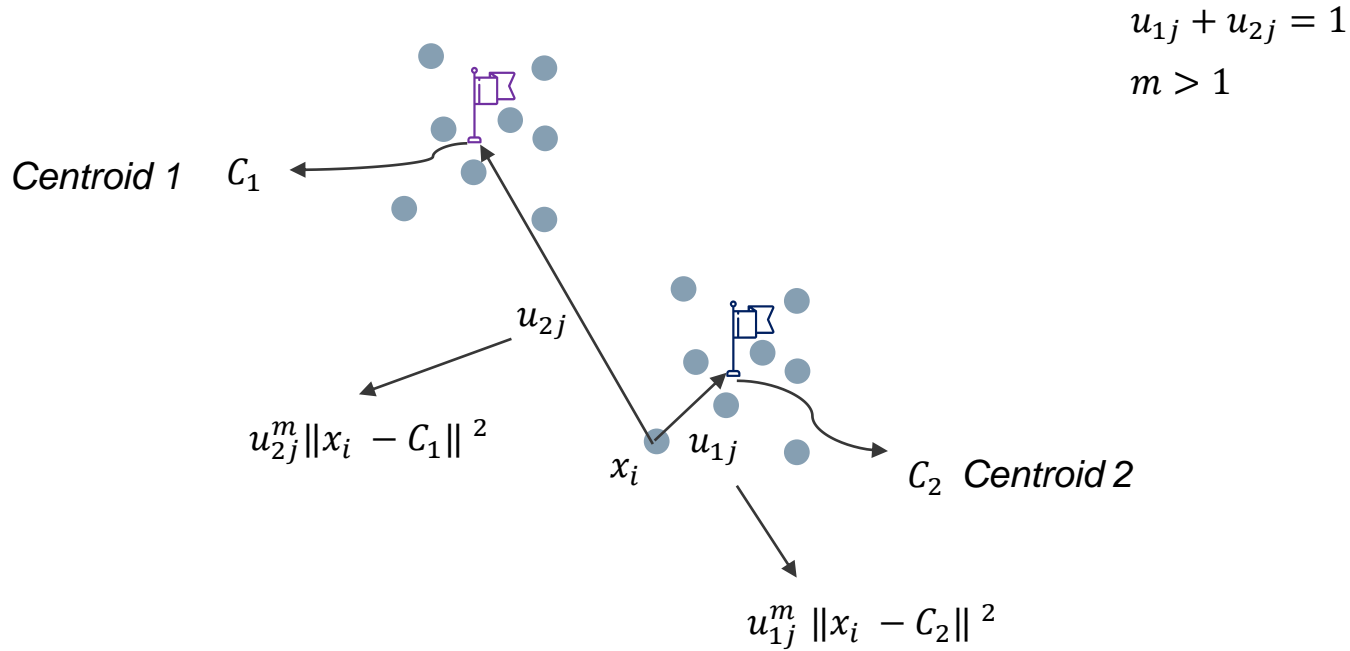
$$\sum_{i=1}^1 u_{i1} = u_{1,1} + u_{2,1} = 1$$

\vdots

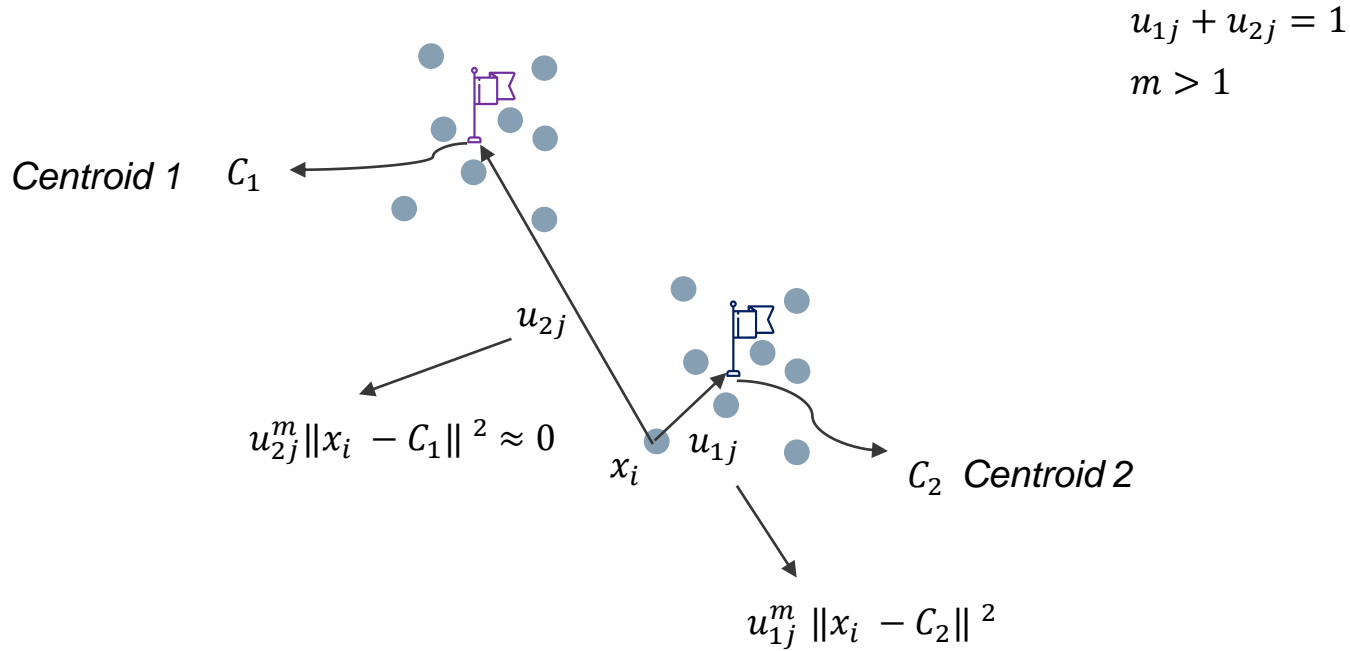
$$\sum_{i=1}^N u_{iN} = u_{1,N} + u_{2,N} = 1$$

$$V_i = \frac{(\sum_{u=1}^n x_i * u_{ij}^r)}{(\sum_{i=1}^n u_{ij}^r)} \quad j = 1, 2, \dots, c$$

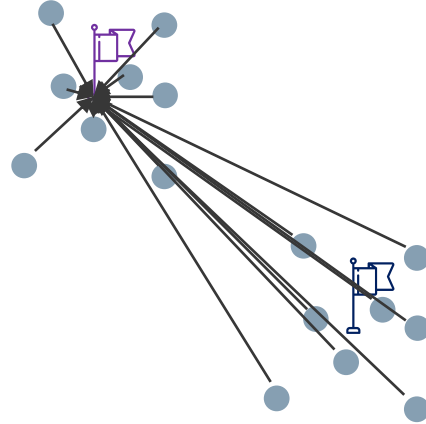
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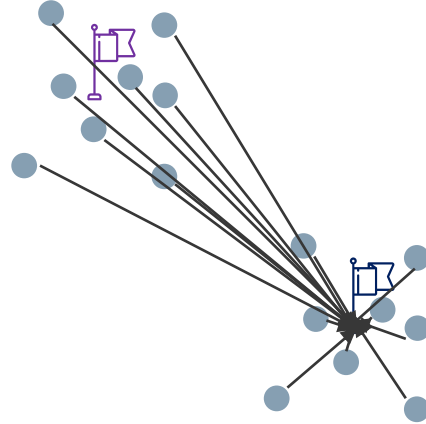


$$u_{1j} + u_{2j} = 1$$

$$m > 1$$

$$\sum_{i=1}^N u_{1j}^m \|x_i - C_1\|^2 = u_{1,1}^m \|x_1 - C_1\|^2 + u_{1,2}^m \|x_2 - C_1\|^2 + \dots + u_{1,N}^m \|x_N - C_1\|^2$$

VISUALIZE

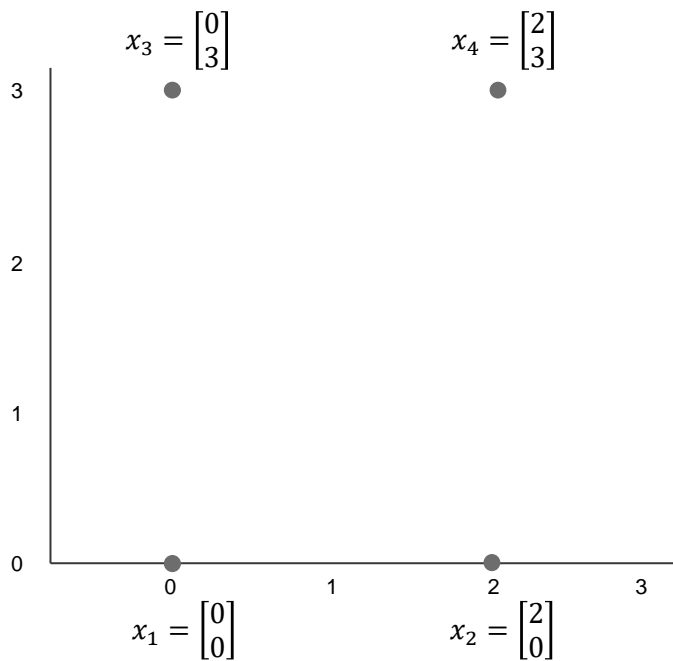


$$u_{1j} + u_{2j} = 1$$

$$m > 1$$

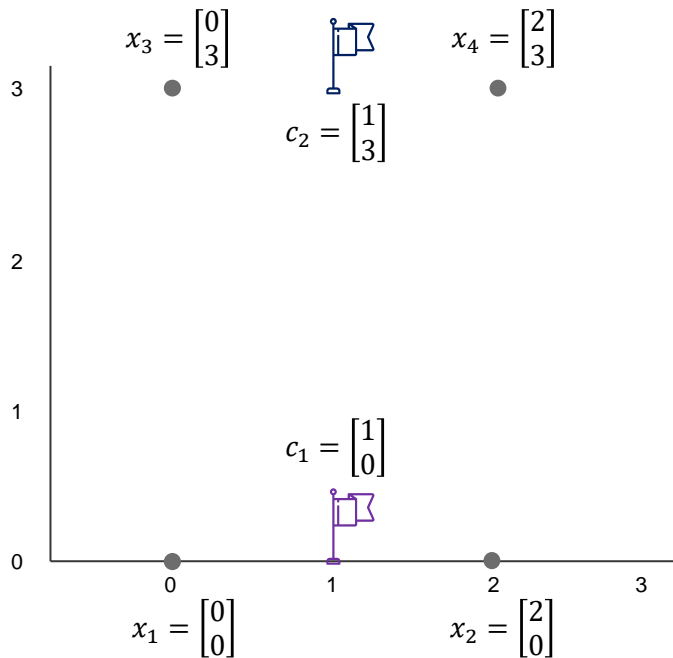
$$\sum_{i=1}^N u_{1j}^m \|x_i - C_2\|^2 = u_{1,1}^m \|x_1 - C_2\|^2 + u_{1,2}^m \|x_2 - C_2\|^2 + \dots + u_{1,N}^m \|x_N - C_2\|^2$$

EXAMPLE



EXAMPLE

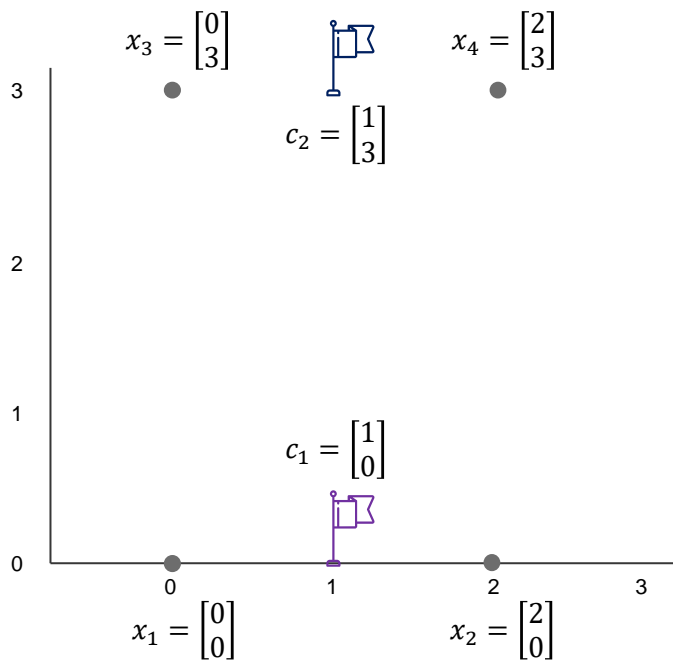
$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$



EXAMPLE

$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

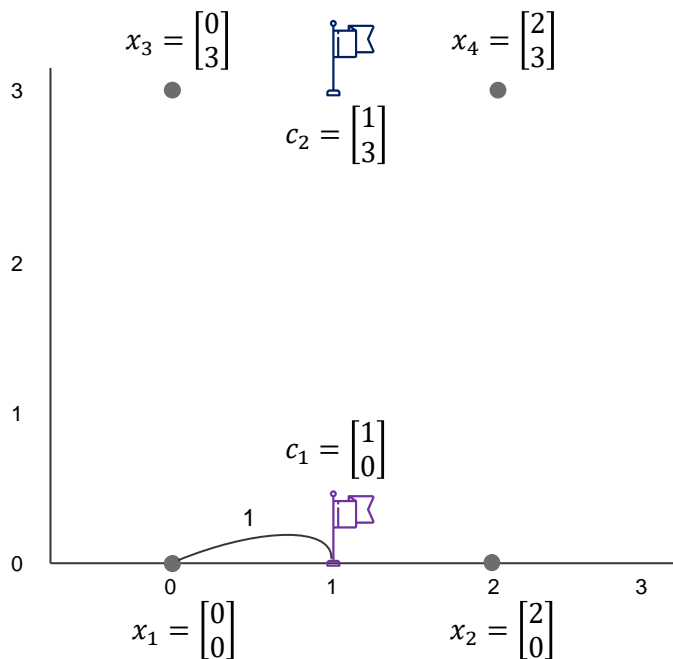
$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$



EXAMPLE

$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

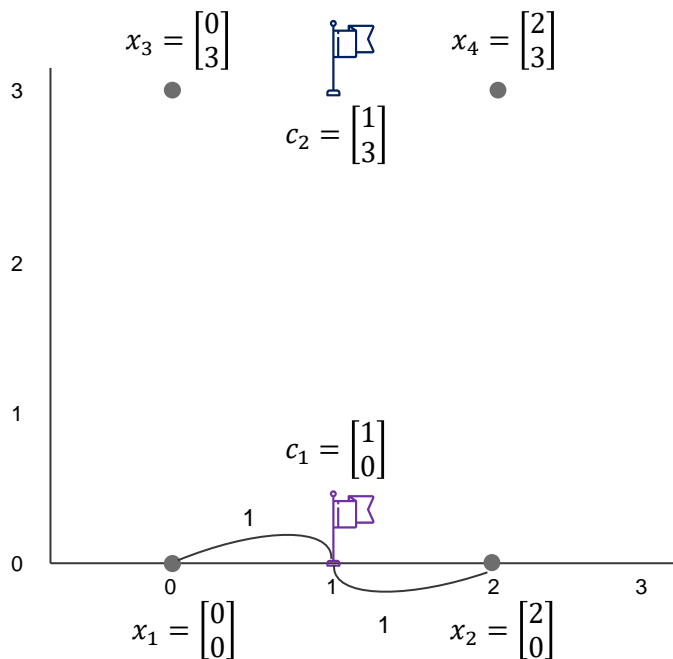
$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$



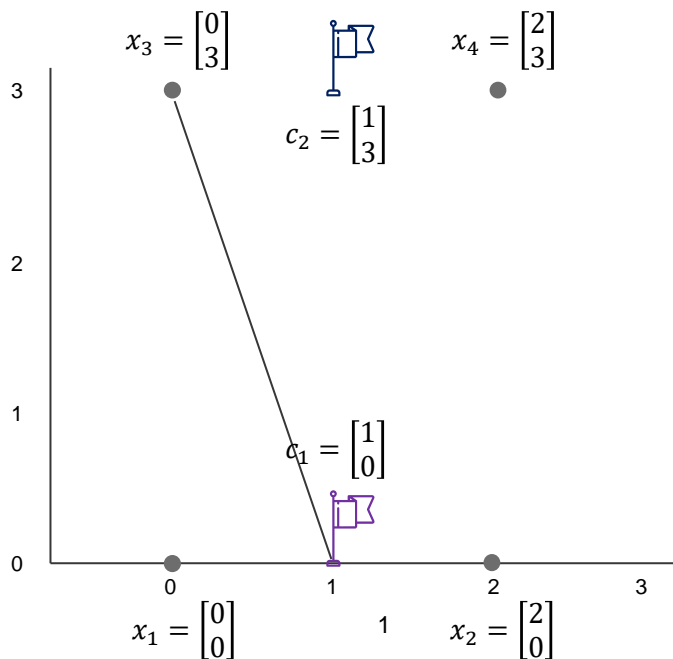
EXAMPLE

$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$



EXAMPLE

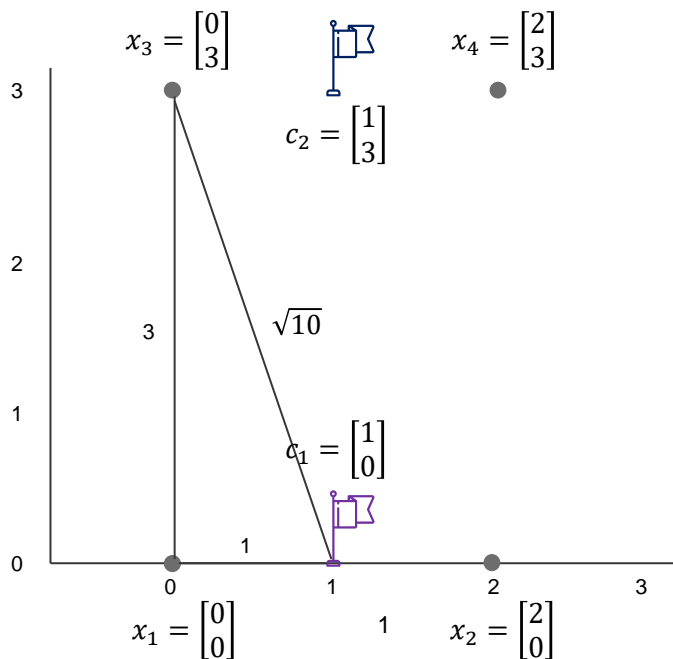


$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$

$$+ u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2$$

EXAMPLE

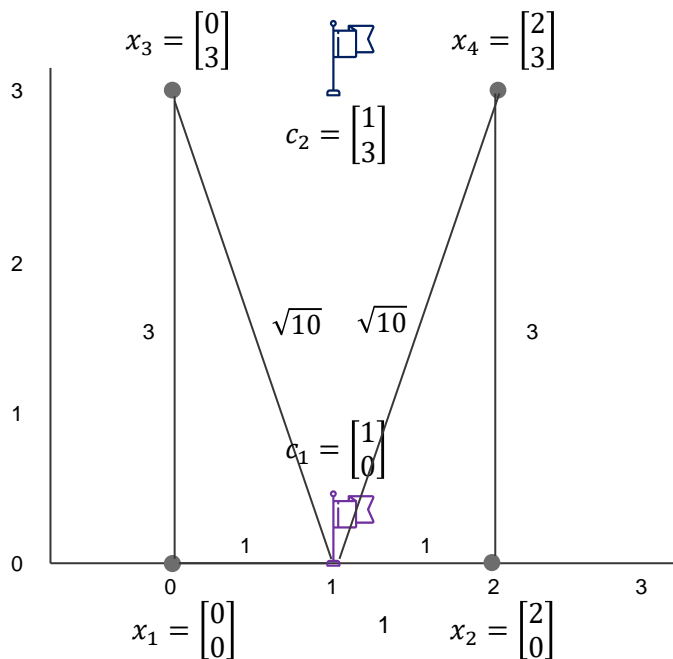


$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$

$$+ u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2$$

EXAMPLE

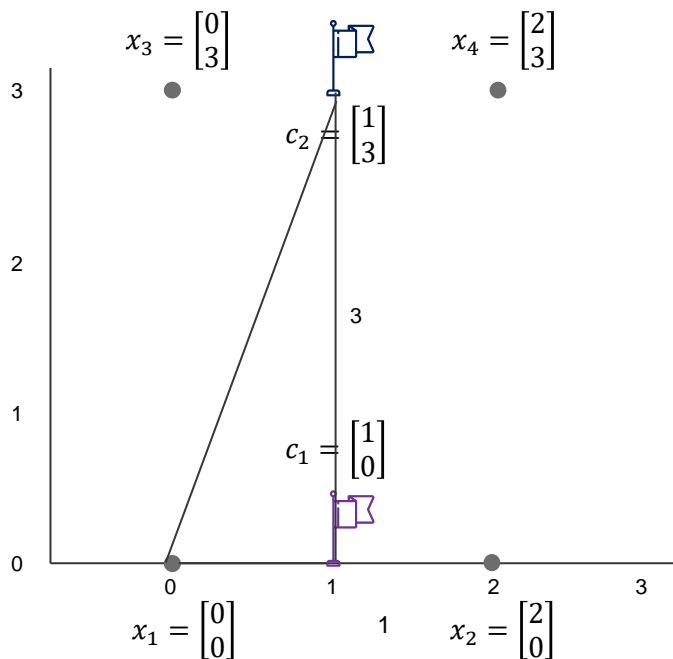


$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$

$$+ u_{1,3}^{10} \|x_3 - c_1\|^2 + u_{1,4}^{10} \|x_4 - c_1\|^2$$

EXAMPLE



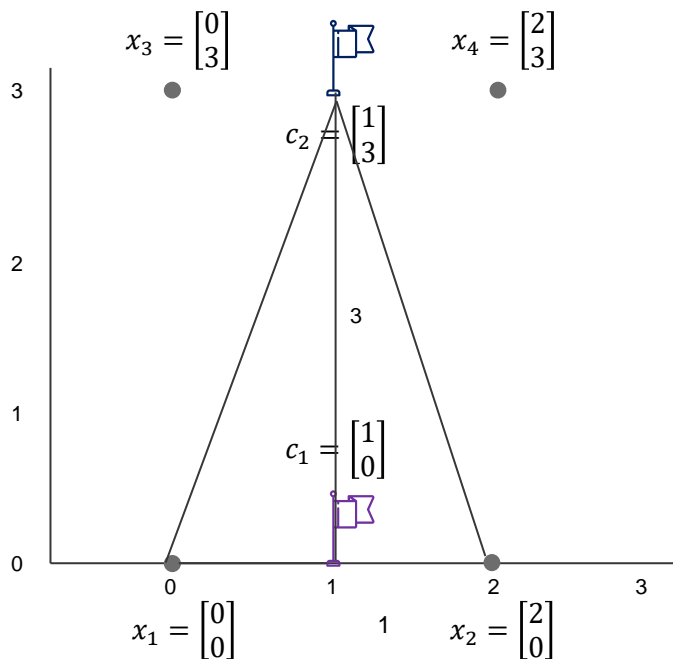
$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$

$$+ u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2$$

$$+ u_{2,1}^m \|x_1 - c_2\|^2 + u_{2,2}^m \|x_2 - c_2\|^2$$

EXAMPLE



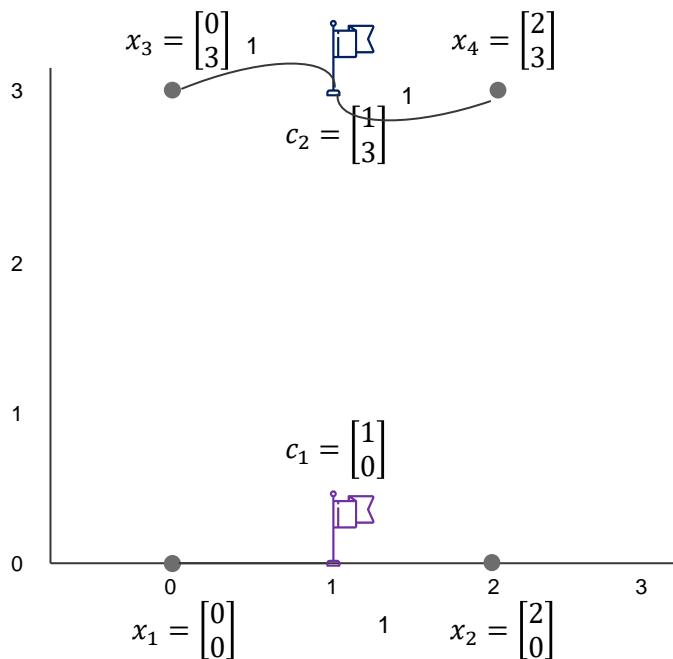
$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$

$$+ u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2$$

$$+ u_{2,1}^m \|x_1 - c_2\|^2 + u_{2,2}^m \|x_2 - c_2\|^2$$

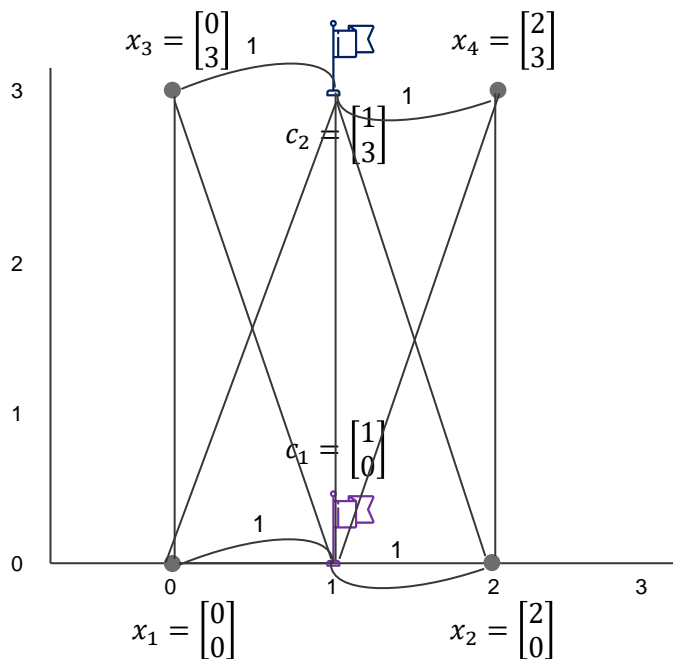
EXAMPLE



$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$\begin{aligned}
 &= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2 \\
 &\quad + u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2 \\
 &\quad + u_{2,1}^m \|x_1 - c_2\|^2 + u_{2,2}^m \|x_2 - c_2\|^2 \\
 &\quad + u_{2,3}^m \|x_3 - c_2\|^2 + u_{2,4}^m \|x_4 - c_2\|^2
 \end{aligned}$$

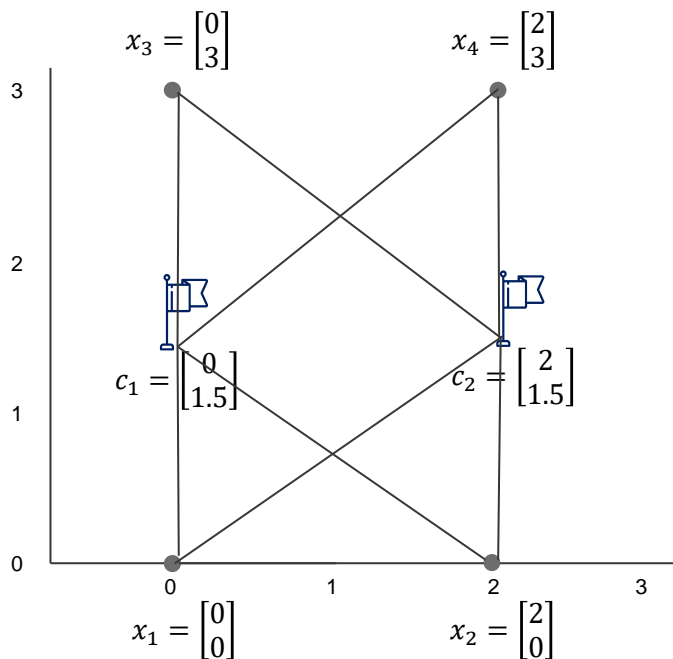
EXAMPLE



$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$\begin{aligned}
 &= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2 \\
 &\quad + u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2 \\
 &\quad + u_{2,1}^m \|x_1 - c_2\|^2 + u_{2,2}^m \|x_2 - c_2\|^2 \\
 &\quad + u_{2,3}^m \|x_3 - c_2\|^2 + u_{2,4}^m \|x_4 - c_2\|^2 \\
 &= 1u_{1,1}^m + 1u_{1,2}^m + 10u_{1,3}^m + 10u_{1,4}^m \\
 &\quad + 10u_{2,1}^m + 10u_{2,2}^m + 1u_{2,3}^m + 1u_{2,4}^m \\
 &= 44
 \end{aligned}$$

EXAMPLE



$$J(u_{ij}, c_i) = \sum_{j=1}^K \sum_{i=1}^N u_{ji}^m \|x_i - c_j\|^2$$

$$= u_{1,1}^m \|x_1 - c_1\|^2 + u_{1,2}^m \|x_2 - c_1\|^2$$

$$+ u_{1,3}^m \|x_3 - c_1\|^2 + u_{1,4}^m \|x_4 - c_1\|^2$$

$$+ u_{2,1}^m \|x_1 - c_2\|^2 + u_{2,2}^m \|x_2 - c_2\|^2$$

$$+ u_{2,3}^m \|x_3 - c_2\|^2 + u_{2,4}^m \|x_4 - c_2\|^2$$

$$= 3u_{1,1}^m + 6.25u_{1,2}^m + 3u_{1,3}^m + 6.25u_{1,4}^m$$

$$+ 6.25u_{2,1}^m + 3u_{2,2}^m + 6.25u_{2,3}^m + 3u_{2,4}^m$$

$$= 37$$

NOW WHAT

- Two paths to take once the cost function has been minimized.
 - Set the maximum membership value to 1 for each point. This turns the fuzzy clustering into a hard clustering where values are 0 and 1.
 - Allows the use of overlapping clusters since the same point has membership values for each cluster.
 - We don't want to always say that a point is assigned to a particular cluster 100% of the time.
 - We might not want to force a point to a singular cluster... knowing that a point can be associated with multiple clusters can be helpful.